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Online identification for batch processes in closed loop incorporating priori controller knowledge

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ABSTRACT

It is of great importance to develop an online modeling method for chemical processes operated in closed loop for better understanding, monitoring the process or other purposes without endangering the system. This paper intends to devise an online system identification method, particularly for the batch process, by fully exploiting its intrinsic repetitiveness. It properly uses the information from the time direction and the batch direction, thus leading to a gradual performance enhancement. In addition, the identification method formulates the *priori* controller knowledge such as closed-loop stability as optimization constraints to refine the parameter estimates. A trust region method is employed to overcome the significant computation burden of directly handling these constraints such as solving Lyapunov inequalities. An adaptive filter is introduced to further smooth the parameter estimates. Finally, the effectiveness of the approach is verified by three numerical examples including a two-tank system.

1. Introduction

Dynamic mathematical models play a pivotal role in chemical engineering, especially in process control, as they provide engineers a precise evolutional picture of the process of interests, which renders the future performance improvement possible, such as redesigning controllers or set points. Generally speaking, dynamic mathematical models are mechanism-based, data-based or a mixture of the both. Mechanism-based models link the process input and output by invoking fundamental physical or chemical principles, e.g., mass conservation, with a bunch of ordinary differential equations (ODEs) or partial differential equations (PDEs). These equations are generally difficult to solve, or it lacks efficient methods to solve them; that makes some advanced control or monitoring strategy intractable, like adaptive control (Åström and Wittenmark, 2013; Ioannou and Sun, 2012; Slotine and Li, 1987; Craig et al., 1987; Mosca, 1995), model predictive control (Mayne et al., 2000; Qin and Badgwell, 2003; Camacho and Alba, 2013; Morari and Lee, 1999; Chen and Allgöwer, 1998), etc. Unlike mechanism-based models, data-based models take a different approach to circumvent these problems, by only focusing on the relationship between process input and output instead of emphasizing the real mechanism between them. In the discipline of process control, the methods to build dynamic data-based model are called *system identification*. There are two categories of system identification methods according to the operation condition of the plant under investigation – open loop and closed loop. In the past decades, lots of interesting results have contributed to the open-loop system identification, no matter in theory (Ljung, 1987; Söderström and Stoica, 1988) or in application (Zhu, 2001; Huang and Shah, 2012; Ikonen and Najim, 2001).

However, in reality, there are many situations where open-loop identification is difficult to implement or even not a feasible option. The simplest example to illustrate this is a plant exhibits integral behaviour, or has open-loop pole(s) in the right half complex plane (in the continuous-time sense). In this particular case, the plant's output always has an unbounded trend for almost any input signal; that compromises the identifiability of the open-loop identification and necessitates the closed-loop identification without jeopardizing the plant's normal operation (Landau and Karimi, 1997). The closed-loop identification also provides room for controller tuning or controller redesign to further improve control performance. Motivated by these reasons, closed-loop identification has aroused lots of attention in control community. From the aspect of frequency analysis, Gustavsson, Ljung and Söderström deeply discussed the fundamental problem of closed-loop identification – identifiability (Gustavsson et al., 1977; Ljung, 1987; Söderström and Stoica, 1988). Zang, Hjalmarsson, Van den hof, and their colleagues studied the connection between identification in closed loop and controller redesign in the frequency domain

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(Zang et al., 1995; Hjalmarsson et al., 1996; Van Den Hof and Schrama, 1995). Forssell and Ljung categorized and analyzed prediction error method in a unified framework (Forssell and Ljung, 1999). Huang and Shah developed a two-stage method and implemented it on a pilot-scale process (Huang and Shah, 1997). On the other hand, from the perspective of time domain, Landau and Karimi developed various recursive identification methods by duplicating the system and comparing the output error (Landau and Karimi, 1997, 1999). Huang, Qin, and their coworkers developed closed-loop subspace identification method based on whitening the error (Huang et al., 2005; Qin and Ljung, 2003).

In this paper, our primary contribution is to devise a closed-loop identification algorithm, particularly for batch process. It is known that batch process, different from continuous process, has its unique dynamic properties such as time variation (Yang and Gao, 2000). Thus, directly applying the aforementioned methods to batch process may not yield satisfactory identification results. For instance, suppose that a plant $y(t) = G(t, q^{-1})r(t)$ is operated perfectly under a certain controller with $r(t)$ as its reference signal. If using prediction error method to identify the plant, the prediction error is comprised of two components: one is from the mismatch of parameter estimates, the other is from the dynamics variation. This can be seen from $\epsilon(t) = y(t) - \hat{y}(t|t-1) = [G(t, q^{-1}) - G(t-1, q^{-1})]r(t) + [G(t-1, q^{-1}) - \hat{G}(t|t-1, q^{-1})]r(t)$. A plausible approach to resolve the problem is to exploit the repetitiveness of batch process, which borrows the idea from *iterative learning control (ILC)*, using the information from two directions – time direction and batch direction. To be specific, the prediction error will be $\epsilon_k(t) = y_k(t) - \hat{y}_k(t, k|k-1) = [G_k(t, q^{-1}) - G_{k-1}(t, q^{-1})]r(t) + [G_{k-1}(t, q^{-1}) - \hat{G}_{k|k-1}(t, q^{-1})]r(t)$; the first term will disappear since $G_k(t, q^{-1}) = G_{k-1}(t, q^{-1})$.[1] Similar literatures are: Ma and Braatz studied offline identification methods for batch process (Ma and Braatz, 2003); Tayebi (2004) and Chi et al. (2008) used the ILC idea but without considering transient identification performance; our previous paper (Cao et al., 2014) has only discussed the open-loop case.

The second contribution of this paper is that we use the *priori* closed-loop knowledge to refine the parameter estimates. As pointed out in our previous work (Cao et al., 2014), the identification results directly generated by two-time dimensional identification algorithm entails severe variation on parameter estimates; to some extent, it contradicts the fact that most chemical processes have slow dynamic variations. The technique – soft constraint – has been employed to tackle this problem in our previous work (Cao et al., 2014); whereas in this paper, we intend to impose "hard" constraints instead. These constraints are formulated from the *priori* closed-loop knowledge. A straightforward example is that the closed-loop poles are all within the unit disk, which follows from the closed-loop stability. Unfortunately, these constraints usually appear as Lyapunov inequalities, a non-convex form or computationally unfriendly. Thus, a *trust region method* is taken advantage of to circumvent this challenge. To ensure the recursive feasibility, the "size" of the trust region is recursively estimated by the techniques developed in robust control. Interestingly, the "size" estimation process and the identification process can run in parallel. In addition, an adaptive low-pass filter is introduced to further neutralize the variation; in the mean time, the filter does not compromise the established recursive feasibility.

The paper is organized as follows: Section 2 derives the unconstrained closed-loop identification methods based on *minimum prediction error methods (MPE)*; Section 3 refines the parameter estimates by imposing constraints formulated from the *priori* closed-loop knowledge; Section 4 analyzes the projection property and recursive feasibility; Section 5 verifies the proposed method by presenting three numerical examples; Section 6 draws a conclusion.

Notations: t and k stand for time and batch index respectively. q^{-1} represents a unit time backward shift operator. $\|\theta\|_{\mathbf{M}} = \sqrt{\theta^T \mathbf{M} \theta}$ is the Euclidean norm. The hat ($\hat{\bullet}$) means estimation or something associated with estimates. $\otimes$ is the Kronecker product. **vec** is the vectorization operator. T signifies transposition. $\lambda_{\max}(\bullet)$, $\rho(\bullet)$ are the maximum eigenvalue and spectral radius of ($\bullet$) respectively.

2. Unconstrained closed-loop identification

2.1. Closed-loop output prediction

Within the paper, we assume that a batch process can be delineated by the following discrete-time *autogressive exogenous (ARX)* model,

$$A(t, q^{-1})y_k(t) = B(t, q^{-1})u_k(t) + e_k(t), \tag{1}$$

where $y_k(t)$ and $u_k(t)$ are, respectively, the plant's output and input at time t of the kth iteration. $e_k(t)$ is a two dimensional white noise, with

$$\mathbb{E}[e_k(t)e_m(n)] = \sigma^2 \delta_{k,m}\delta_{t,n}.$$

$\delta_{k,m}$, $\delta_{t,n}$ are Kronecker deltas, and $\delta_{k,m} = 1$ if and only if $k = m$. $A(t, q^{-1})$ and $B(t, q^{-1})$ are scalar polynomials with time varying coefficients as shown in the following equations,

$$A(t, q^{-1}) = 1 + a_1(t)q^{-1} + a_2(t)q^{-2} + \cdots + a_{na}(t)q^{-na}, \tag{2a}$$

$$B(t, q^{-1}) = b_1(t)q^{-1} + b_2(t)q^{-2} + \cdots + b_{nb}(t)q^{-nb}. \tag{2b}$$

Here $a_1(t)$, $a_2(t)$, …, $a_{na}(t)$ and $b_1(t)$, $b_2(t)$, …, $b_{nb}(t)$ are the time varying coefficients to be identified. na, nb are the polynomial orders. In the paper, it is assumed that these orders are exactly known. It is necessary to put two remarks on the plant model in (1). First, in reality, most batch processes exhibit certain nonlinearity. However, in many cases, the plants are required to track a given set point trajectory; the objective is usually achieved by a feedback controller. This fact provides process control engineers sufficient rationales to approximate the real dynamics in the proximity of the trajectory with a *linear time varying (LTV) model*, i.e., (1). Second, from (2b), it is assumed that the input delay order (nd) is equal to 1. This assumption does not impose any restriction. Because it is trivial to extend to $nd = d$ case by treating first $d - 1$ coefficients in (2b) as zero. The ARX model has been assumed, because it is simple and enough to capture batch processes' dynamics in practice, for example, the work of Yang and Gao on injection molding (Yang and Gao, 2000).

Furthermore, assume that the plant in (1) is operated in closed loop to track a given reference by an *R-S-T* controller (a two-degree-of-freedom controller). This type of controller has been reported widely applied in controller analysis, i.e., Landau and Karimi (1997, 1999). The block diagram of the closed loop is shown in Fig. 1. The associated control law is given as

$$u_k(t) = -\frac{R(q^{-1})}{S(q^{-1})}y_k(t) + \frac{T(q^{-1})}{S(q^{-1})}r_k(t). \tag{3}$$

Here $r_k(t)$ is the reference signal; it can be decomposed into two components like $r_k(t) = r_r(t) + r_{nr,k}(t)$. $r_r(t)$ is the repetitive component that the system is required to follow; $r_{nr,k}(t)$ is the non-repetitive part with relatively small magnitude to provide the system with sufficient excitation. nr, ns and nt correspond to the orders of scalar polynomials $R(q^{-1})$, $S(q^{-1})$ and $T(q^{-1})$. Without loss of generality, the polynomial $S(q^{-1})$ is given in the canonical form, i.e., $S(q^{-1}) = 1 + S^*(q^{-1})$, where $S^*(q^{-1}) = s_1 q^{-1} + \cdots + s_{ns}q^{-ns}$.

[1] k stands for batch index, which can also be called iteration index or period index.